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A lean assessment tool based on systems dynamics

Oleghe Omogbai, Konstantinos Salonitis*

Manufacturing Department, Cranfield University, Bedfordshire, MK43 0AL, England
* Corresponding author. Tel.: +44-1234-758347. E-mail address: k.salonitis@cranfield.ac.uk

Abstract

Lean manufacturing is synonymous with a set of practices used in the identification and elimination of waste related with the manufacturing system, and focusing on what creates value for the customer. Lean assessment tools enable an overall audit of the performance of lean practices, and so are able to identify lean improvements. The interactions between lean practices and their improvements are often latent and need to be investigated: a systems approach can be used to disclose these hidden interactions. In this article, system dynamics is used as a lean assessment tool to assess and improve lean performance for a print packaging manufacturing system.

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Keywords: Lean manufacturing; lean assessment tool; system dynamics

1. Introduction

Lean manufacturing (LM) as a set of practices, tools and techniques is centered around five core principles namely: precisely determining the value of each specific product in the eyes of the customer; identifying the value flow of each product; making the value flow continuously; letting the customer pull value from the manufacturer and seeking perfection [1]. The intended end-result is improved organizational performance through customer value enhancement as a result of waste (non-value adding activities) elimination. Representative practices relating to LM include just in time (JIT) management, total productive maintenance (TPM), employee involvement, continuous improvement, set-up reduction, customer engagement and many others.

For an organization to enjoy the multiple benefits of LM, the practices associated with it need to be implemented holistically [2]. A lean assessment tool (LAT) is typically used to audit, in a simultaneous fashion, the performance of all the lean practices that are relevant to the type of organization.

Many LATs have been developed and validated. Qualitative questionnaire-type models such as the Lean Enterprise Self-assessment tool (LESAT), Balanced Scorecard, European Foundation for Quality Management (EFQM), Malcolm Baldridge Model, and the Shingo Model [3] have been used as the basis for a LAT. Quantitative based LATs also exist such as Value Stream Mapping (VSM) and many others [3].

Lean practices affect and are affected by other practices. The case of routine maintenance is an example. Routine maintenance is an arm of TPM and can be described as the type of maintenance undertaken daily by operators on their machines. Such maintenance include cleaning, lubricating and inspecting of machines. Increasing the number of routine maintenance should naturally have a positive effect by reducing the frequency of machine breakdowns. However, carrying out routine maintenance results in the machine being non-operational during the checks, thereby increasing machine downtime and delaying manufacturing cycle time. This and many other interactions occur between improvement lean practices.

The non-consideration of the interrelations between lean practices has made LATs to be less than optimal [4]. Few researchers have considered this relationship [4,5,6] in their LAT. However, they have done so using subjective-based approaches such as Analytical Hierarchy Process (AHP) [4], Analytical Network Process (ANP) [5] and BSC [6]. Subjective based approaches have the flaw of bias, and a strategic and long-term view based on small incremental lean improvements cannot be achieved. An objective-based approach has previously been attempted using discrete event simulation (DES) [7], but focused mainly on tangible aspects of LM such as reduction in setup, defect rates and lead-time.

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In the current paper, a System Dynamics (SD) based LAT incorporating both tangible and behavioral aspects of LM is proposed. It is used to objectively investigate the dynamic interactions between lean practices, their performance outcomes and other system variables. The approach is further applied to generate an optimized setting of lean improvements that are needed to minimize manufacturing lead-time, using an optimization add-on tool of the SD simulation software.

2. Systems dynamics modeling approach

SD is "a perspective and set of conceptual tools that enable us to understand the structure and dynamics of complex systems" [8]. It uses simulation to investigate how a system will respond, dynamically, to a set of changes [9].

The use of SD has been well researched within manufacturing systems and quite a number are lean-related. SD has been used to control the cost of quality [9], to investigate the performance of a lean cell under uncertainty [10], to improve the performance of a foundry operation [11] and as a productivity improvement tool in a print shop [12]. It has also been used as a dynamic LAT for takt time improvement [13]. In the current study, SD is used to examine multiple aspects of lean as well as their interactions.

SD is a modeling technique, consisting of a stock and flow diagram (SFD). The SFD is a causal loop diagram, which maps the essential variables of the system under review (lean practices in the current article) and the causal influences between them. Stocks are accumulations, expressed in quantities that characterize the system [14], for example inventory and works-in-process (WIP). Flows are rates, typically in quantities over a specified time, which deplete or replenish the "stock" level, such as shipment rate and production rate respectively for a manufacturing system.

An SFD on its own cannot be simulated. It needs a set of governing equations that describe the various causal relationships [15,16]. Subsequently, the SFD can be used for scenario analysis, optimization, and other simulation analysis/applications. Several guidelines to using SD can be found in [8]. In the current paper, a manufacturing case study is used for a better illustration of the SD modeling approach for lean assessment.

3. Case study illustration

The production operations of a print packaging manufacturer have been used as a case study. The organization has been implementing lean practices for a few years and seeks to investigate the interactions between proposed lean improvements. The prior knowledge about these interactions is needed to design an optimal set of lean improvements for the company.

The printing industry is a make-to-order (MTO) production system with custom products [12]. Top on the list of customer-specified values for the print industry is dependability [17]. On-time or before-time deliveries makeup a dependable print packaging supplier. The primary concern of the company is to meet up with customer delivery time. Lead-time minimization has therefore been chosen as the primary objective of the proposed lean improvements. SD is used to articulate the problem in a dynamic way so that the organization can validate proposed lean improvements as well as study the interactions between them.

3.1. Stock and flow diagram

Activities and outcomes relating to three lean practices have been chosen: Total Productive Maintenance (TPM), Quality Management (QM) and Employee Morale. Although many others can be investigated alongside these, the three chosen are pertinent to the problem and are sufficient enough to illustrate the intended approach.

An SFD (Fig. 1) is first developed for the case. AnyLogic 7.2 SD Software was used for the study. The problem is modeled around two main stocks: job order backlog and defects. Job order backlog is the outstanding work that is replenished with new order through *job entry rate* and depleted through *throughput*. *Defects* cannot be depleted and are accumulated through *defect rate.*

The *number of job orders* and *the time between orders* influences *Job order entry rate*. When the *number of job orders* increases, the *variety of WIP* increases because each job order is unique and is typical of MTO systems. If the *variety of WIP* increases, there are more *setups and changeovers* than when few and similar jobs are in constant production. When a machine is being setup and changed over for a job, the machine is not processing, but stalled. The more there are *setups and changeovers* in the system, the more machines are stalled and this increases the *production idle time*.

When there is an increase in *total job orders* the pressure to maintain customer specified lead-time is increased. *Lead-time pressure* affects the routine maintenance as management aims to minimize downtime during routine services. In addition, *work hours* are increased to ensure lead-time is not adversely affected, but this is to a maximum of 11 hours per day (work hours are flexible for the plant ranging between 8 and 11-hour days depending on work load). With increased work hours, *employee fatigue* sets in, which reduces the number of routine *quality checks* and productivity through *employee output per time*. If employee output drops, then *throughput* also drops. Various *process errors* are generated whenever employees are fatigued for example mistakes with mixing printing inks.

When the stock of defects increases, the plant over produces to account for increased defects in the process. This is anti-lean but inevitable since the plant is expected to meet with the specified job order quantity. However, the company seeks ways to eliminate this as part of their lean transformation. The *overproduction for defects* affects the needed *throughput* to ensure job order completion is on target. Other lean practices and system variables are depicted in the SFD (Fig. 1).

Usually each arrow in the SFD is denoted by a "+" or "-" characterizing if the "cause" and "effect" variables change in the same direction or not. For the purpose of de-cluttering the SFD, these signs are sometimes omitted.

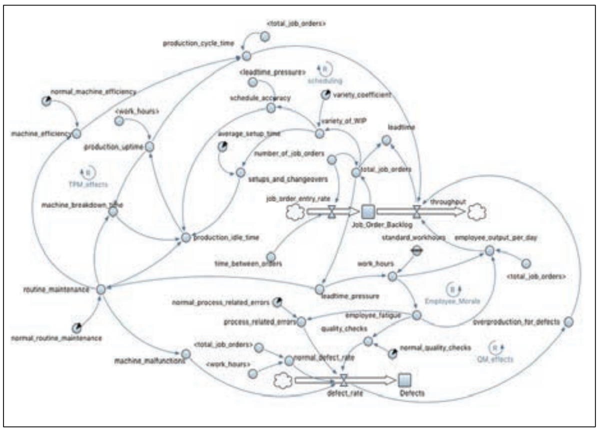


Fig. 1. Stock and flow diagram for the case study

Feedback loops characterize the structure of the system and describe how the system reacts to change [8]. The key feedback loops were identified within the model- TPM effect, QM effect and Employee Morale. A feedback loop is identified as reinforcing (R) if a change in a variable is reinforced when traced round the loop back to the variable.

It is a balancing (B) loop if the change is opposed. As an example, if *routine maintenance* drops, *machine efficiency* drops, and time losses are generated subsequently through *production cycle time* and *throughput*, which then increases *lead-time pressure* and eventually *routine maintenance* is reduced so that machine stalled time is minimized.

3.2. Governing equations for causal relationships

With the SFD, the model is structurally complete, but cannot be simulated: it needs a set of equations that describe the various causal relationships [15]. Table 1 contains equations used in the SFD model.

Establishing the causal equations requires a combination of theory, experiment, observation [8], intuition and knowledge about the relationship between the cause and effect variables. As an example *job order entry rate* is the *number of job orders* divided by the *time between orders*. The *variety of WIP* is a factor of the total WIP (*total job orders*) in the system, which includes *job order backlog* and *number of job orders* (that have newly entered the system).

The use of historical data is also indispensable. Archival data can be extracted from recorded or observed statements and fed into table functions to represent non-linear relationships. Table functions are standard tools in SD software packages. Non-linear relationships are specified as a table of values for the cause and effect variables [8]. As an example, the relationship between *employee fatigue* and *process related errors* is represented as:

process related errors = *f*(employee fatigue) (1)

If *process related errors* is defined by Y and *employee fatigue* by X then [8]

Table for effect of X on Y = (x_1,y_1), (x_2,y_2)….(x_n,y_n) (2)

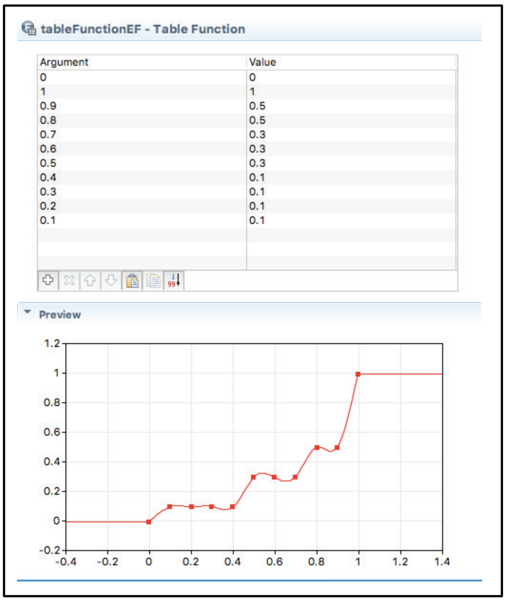
where (x_i,y_i) represents each pair of points (of normalized values) defining the relationship [8]. Table functions can capture purely behavioral influences [8], the type that exists between many variables in the real system, for which an analytical function cannot be defined. Fig. 2 is the snapshot of the Table Function (tableFunctionEF) generated in AnyLogic, defining the relationship between *employee fatigue* and *process related* errors.

The non-linear relationship shows how *employee fatigue* increases *process related errors*, represented at "argument" and "value" respectively in AnyLogic. Managers in the case organization provided the information to generate the data in the Table (Fig. 2). Each row in the Table represents the process related errors (value) for the corresponding employee fatigue (argument). Both sets of data have been normalized with respect to a scale of 0 to 1. As an example, it has been observed in the plant that when employee fatigue is low at a factor of 0.2, process related errors are also low at a factor of 0.1. The first two rows in the Table represent bounded values. The graphical representation of the data set is shown as the bottom diagram of Fig. 2.

Eq. 3 defines the governing equation for process related errors after configuring the table function for the relationship between it and employee fatigue.

process related errors = *tableFunctionEF(employee fatigue)* (3)

Table 1 contains some of the other equations used in the SD model. The model was configured with cyclical demand patterns to represent the high and low demands for the company's products. Model units include orders, day (time) and orders/day (rates). Dimensionless units representing percentages and ratios are also used.


tableFunctionEF - Table Function

Argument	Value
0	0
1	1
0.9	0.5
0.8	0.5
0.7	0.3
0.6	0.3
0.5	0.3
0.4	0.1
0.3	0.1
0.2	0.1
0.1	0.1

Fig. 2. Screen shot showing example table function in AnyLogic, used to represent the non-linear relationship between employee fatigue and process related errors

3.3. Lean assessment using the SD model

The main aim of this article is to generate a SD model for lean assessment and verification/validation of SFD achieves this. After inputting the governing equations, the model is then run and verified against the real life dynamics of the case organization using the reference mode. The reference mode is a pattern of system behavior over time [15]. In the current analysis, the reference mode supports the hypothesis that variations exist within the system performance parameters when demand fluctuates between high and low values. The SD model is run for one year under current conditions. Fig. 3 (a-d) shows the model run results for lead-time (Customer Delivery Performance), defect rate (TQM), employee fatigue (Employee Morale) and machine efficiency (TPM) and verifies the variations in lean performance in accordance with demand loads.

The graphs in Fig. 3 are indicative of the lean performances for the system for one year under current conditions, and assuming no changes to lean parameters. For example, Employee Morale (Fig. 3c) ranges between 0.7 and 0.85 on an increasing scale of 0 to 1, where 1 represents the highest level of employee morale. Machine efficiency is a typical measure for TPM and ranges between 40% and 60% (Fig. 3d).

Table 1. Equations used in the SD model

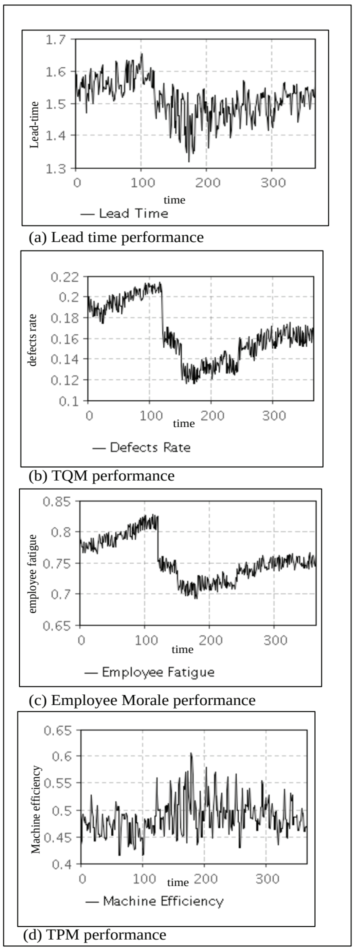
Variable	Equation
job order entry rate	number of job orders / time between orders
time between orders	1
total job orders	Job Order Backlog + number of job orders
d(Job Order Backlog)/dt	job order entry rate - throughput (initial value=25)
variety of WIP	total job orders / variety coefficient
variety coefficient	uniform discrete (3,9)
average setup time	Uniform (0.0042,0.0083)
setups and changeovers	variety of WIP * average setup time
production idle time	schedule accuracy * (setups and changeovers + routine maintenance + machine breakdown time)
routine maintenance	normal routine maintenance / lead-time pressure
production idle time	schedule accuracy * (setups and changeovers + routine maintenance + machine breakdown time)
normal defect rate	0.1 * total job orders / (work hours * 8)
throughput	(production cycle time + employee output per day)/2 - overproduction for defects
employee output per day	(total job orders / work hours) * employee fatigue
defect rate	((quality checks + process related errors + machine malfunctions) / 3) * normal defect rate
overproduction for defects	defect rate
d(Defects)/dt	defect rate (initial value=0.001)
quality checks	Normal quality checks / employee fatigue

4. Interactions between lean practices

In this section the model is simulated under various extreme conditions to investigate the interactions between lean practices and their performances. Altering the values of parameter variables in the model achieved this. Parameter variables are not affected by other variables and are used to adjust model behavior. The authors of the present article set out to alter the values of parameter variables in the model as listed in Table 2.

The values presented in Table 2 are the extreme best values for the case study under analysis. For example normal routine maintenance for the current system is uniformly distributed (0.017, 0.05) i.e. routine maintenance is done once randomly anywhere from 20 days (0.017) to 58 days (0.05). For Experiment 1, the test value is set at 0.02 i.e. routine maintenance is fixed at once every five days.

Figures 4-6 are the simulation results for the three experiments. The simulation results show marginal interactions between setup time reduction, reduction in process related errors and improvements in routine maintenance.



(a) Lead time performance
(b) TQM performance
(c) Employee Morale performance
(d) TPM performance

Fig. 3. Current state lean performances for (a) lead-time, (b) TQM, (c) Employee Morale, (d) TPM

5. Optimization experiments to achieve lean objective

An optimization experiment was undertaken to establish the optimal set of lean parameters to minimize lead-time. Table 3 summarizes the parameter values for the optimization experiment and represents values for current system parameter variables. The SD model was run with the optimization add-on function of the AnyLogic software, and the results are presented in Fig. 7 for 250 iterations. The optimization results did not change beyond this number of iterations.

Table 2. Parameter values for simulation experiment with the SD model

Exp.* No.	Variable	Current Value	Exp. Value	Description of experiment values
1	normal routine maintenance	Uniform (0.017, 0.05)	0.2 days	Time between maintenance is once every five days
2	normal process related errors	Uniform (0.15, 0.25)	0.02	2 % of orders have process related errors
3	average setup time	Uniform (0.0042, 0.0083)	0.003 days	Average setup time in day units

*Experiment

Table 3. Parameter values for lean optimization experiment

Parameter	Type	Value	
		Min.	Max.
variety coefficient	discrete	3	9
average setup time	continuous	0.004	0.008
normal machine efficiency	continuous	0.7	0.8
normal routine maintenance	continuous	0.017	0.05
normal process related errors	continuous	0.15	0.25
normal quality checks	continuous	0.1	0.2

6. Study inferences and implications

The primary purpose of this article was to articulate a methodology to objectively investigate the interactions between lean improvements. A SD approach was used to achieve this through simulation modeling and experimentation. The experiments conducted with the SD model in section 4 indicate that lean improvements for the case study do not interact significantly. In other words, a decrease in average setup time for the case has little effect on defect rate and employee fatigue for example. It may be difficult to reconcile the latter case, as employee fatigue should naturally increase if there is pressure to reduce setup time. To enable further investigation of the effect of average setup time on employee fatigue, for example, the SD model is simply modified. A causal link between average setup time and employee fatigue can be incorporated into the model. This link, when simulated, will generate the detailed relationship between average setup time and employee fatigue. In reality, SD models are perfected over extended periods to capture more of the causal relationships within the system. The case study organization has used the SD model generated in this article as a base model for their lean assessment studies. The model is also re-useable in other similar instances.

The SD model was used to validate lean improvements. For example, when the SD model is simulated with routine maintenance set at 0.2 days as opposed to the current value that is uniformly distributed (0.017, 0.05), lead-time was shown to improve by approximately 27%. This implies that if the number of routine maintenance is increased, lead-time reduces.

The optimization experiment (section 5) was used to generate an optimal set of values for the parameter variables, needed to minimize lead-time. Results of the optimization experiment, Fig. 7, indicate that the best lead-time of 1.42days is achieved when variety coefficient= 9, average setup time= 0.004, normal machine efficiency= 0.735, normal routine maintenance= 0.03, normal process errors= 0.233 and normal quality checks= 0.174. These values are based on the ranges specified for the optimization experiment (Table 3). Altering the parameter ranges as well as changing the optimization objective function can be used to configure other optimization experiments.

A significant contribution of the current study is that “hard” and “soft” aspects of LM can be assessed and improved in tandem in one LAT. This kind of lean assessment is lacking [18, 19]. For example, measuring Employee Morale is often done using questionnaire-based, subjective-type lean self-assessment tools, while setup and changeovers are tracked using quantitative based LATs such as the VSM. With the SD modeling approach both qualitative and quantitative measures of LM can be accumulated under the same assessment.

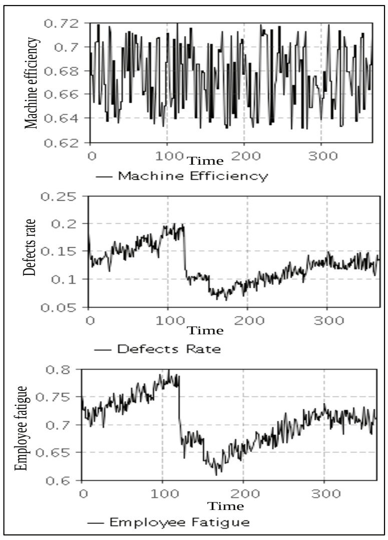


Fig. 4. Simulation results for Experiment 1 with routine maintenance set at a value of 0.2

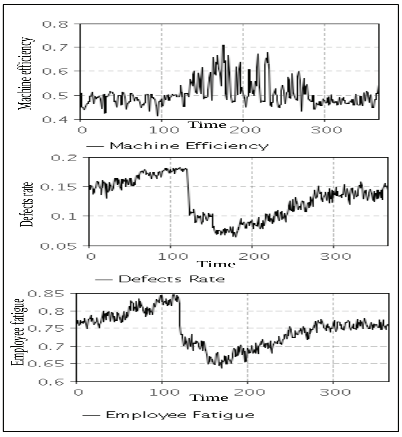


Fig. 5. Simulation results for Experiment 2 with process related errors = 0.02

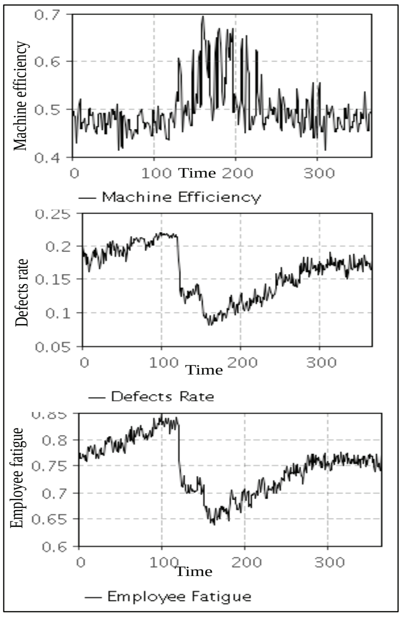


Fig. 6. Simulation results for Experiment 3 with average setup time= 0.003

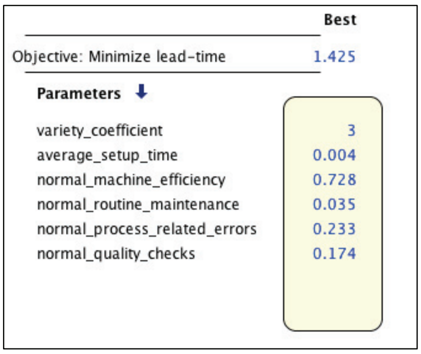


Fig. 7. Snapshot of results of optimization experiment for lead-time minimization

7. Conclusions and future directions

In the current article, a SD based lean assessment tool was generated. The SD modeling approach enabled the validation of proposed lean improvements as well as the analysis of the inter-relationships between lean variables. The model was also used to establish an optimal set of values for lean variables in the system, in order to minimize lead-time. The model developed in this article is a good reference point for manufacturing organizations wishing to model lean practices, lean indices and lean outcomes holistically within the same model, while investigating their interactions.

References

[1] Womack JP, Jones DT. Lean thinking: banish waste and create wealth in your corporation. 2nd ed. New York: Free Press; 2003.

[2] Bonovia T, Marin JA. An empirical study of lean production in the ceramic tile industry in Spain. Int J Prod Op Manage 2006;26:505-531.

[3] Oleghe O, Salonitis K. Leanness assessment frameworks: strengths and weaknesses. Submitted for publication to Journal of Manufacturing Technology Management. 2015.

[4] Wong WP, Ignatius J, Soh KL. What is the leanness level of your organisation in lean transformation implementation? An integrated lean index using ANP approach? Prod Plan Contr 2014;25:273–287.

[5] Cil I, Turkan YS.. 2013. An AHP-based assessment model for lean enterprise transformation. Int J Adv Manuf Tech 2013;64:1113-1130.

[6] Seyedhosseini SM, Taleghani AE, Baksha A, Partovi S. Extracting leanness criteria by employing the concept of balanced scorecard. Exp Sys App 2011;38:10454-10461.

[7] Oleghe OA, Salonitis K. Manufacturing system lean improvement design using discrete event simulation. Accepted for conference proceedings at the 49th CIRP Conference on Manufacturing Systems, Stuttgart, Germany, 25 -27 May 2016.

[8] Sterman JD. Business dynamics: systems thinking and modeling for a complex world. New York: McGraw-Hill; 2000.

[9] Khataie A, Bulgak A. A cost of quality decision support model for lean manufacturing: activity-based costing application. Int J Qual Reliab Manage 2013;30:751–64.

[10] Deif A. Dynamic analysis of a lean cell under uncertainty. Int J Prod Res 2012;50:1127–39.

[11] Rodrigues LLR, Hebbar S, Shetty D, Hoskote RN. Performance improvement of foundry through lean methodology: a modeling and simulation approach. IEEE Computer Society. 7th Asia Modeling Symposium. 2013.

[12] Uribe J. Print Productivity: a system dynamics approach. A Research Monograph of the Printing Industry Center at Rochester Institute of Technology;2008:5

[13] Ali RM, Deif AM. Dynamic lean assessment for takt time implementation. Procedia CIRP 17 2014:577-581.

[14] Grigoryev I. AnyLogic 7 in three days: a quick course in simulation modeling. 2015. Available at http://www.anylogic.com/free-simulation-book-and-modeling-tutorials

[15] Vensim Version 6.3E. Introduction and Tutorial.

[16] Rodrigues LLR, Dharmaraj N. System dynamics approach for change management in new product development. Manage Res News 2006; 29:512-523

[17] Pellow B, Sorce P, Frey F, Oslon L, Moore K, Kirpichenko S. The advertising agency’s role in marketing communications demand creation. Printing Industry Center at Rochester Institute of Technology. 2003:5

[18] Oleghe OA, Salonitis K. Improving the Efficacy of the Lean Index through the Quantification of Qualitative Lean Metrics. Procedia CIRP 2015; 37:42-47

[19] Oleghe OA, Salonitis K. Variation Modeling of Lean Manufacturing Performance Using Fuzzy Logic Based Quantitative Lean Index. Procedia CIPR 2016; 41:608-613

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Omogbai, Oleghe

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